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Machine Learning Homework 2:

Problem 1:

$$y_i \stackrel{\text{ind}}{\sim} N(x_i^T \omega, \lambda^{-1}) \quad \omega \sim N(0, \text{diag}(\alpha_1, \dots, \alpha_d)^{-1})$$

$$\alpha_k = \text{Gamma}(a_0, b_0) \quad \lambda = \text{Gamma}(e_0, f_0)$$

(a)

$$\begin{aligned} g(\lambda) &\propto \exp \left\{ \mathbb{E}_{g(\omega)} [\ln p(y | \omega, \alpha_{1:d}, \lambda, x)] + \ln g(\lambda) \right\} \\ &\propto \exp \left\{ \mathbb{E}_{g(\omega)} \left[\frac{N}{2} \ln(\lambda) - \frac{\lambda}{2} (y - X^T \omega)^T (y - X^T \omega) \right] + (e_0 - 1) \ln(\lambda) - f_0 \lambda \right\} \\ &\propto \exp \left\{ \left(\frac{N}{2} + e_0 - 1 \right) \ln \lambda - \frac{1}{2} \sum_{i=1}^N \left(\mathbb{E}_{g(\omega)} [(y_i - x_i^T \omega)^2] + 2 f_0 \right) \lambda \right\} \\ &\propto \exp \left\{ \left(\frac{N}{2} + e_0 - 1 \right) \ln \lambda - (y^T y - 2 y^T x^T \mathbb{E}_{g(\omega)}[\omega] + \text{tr}(\mathbb{E}_{g(\omega)}[\omega \omega^T] X X^T) + 2 f_0) \lambda \right\} \end{aligned}$$

$$g(\lambda) = \text{Gamma}(e'_0, f'_0)$$

$$e'_0 = e_0 + \frac{N}{2}$$

$$f'_0 = \frac{1}{2} (y^T y - 2 y^T x^T \mathbb{E}_{g(\omega)}[\omega] + \text{tr}(\mathbb{E}_{g(\omega)}[\omega \omega^T] X X^T) + 2 f_0)$$

$g(\alpha_k)$ where $k = 1:d$

$$g(\alpha_k) \propto \exp \left\{ \mathbb{E}_{g(\omega_k)} [\ln p(\omega_k | \alpha_k)] + \ln g(\alpha_k) \right\}$$

$$\propto \exp \left\{ \mathbb{E}_{g(\omega_k)} \left[\frac{1}{2} \ln(\alpha_k) - \frac{\alpha_k}{2} (\omega_k^2) \right] + (a_0 - 1) \ln \alpha_k - b_0 \alpha_k \right\}$$

$$\propto \exp \left\{ \left(\frac{1}{2} + a_0 - 1 \right) \ln(\alpha_k) - \frac{1}{2} \left(\frac{1}{g(w)} [w_k^2] + 2b_0 \right) \alpha_k \right\}$$

$$f(\alpha_k) = \text{Gamma}(a_o^{(k)'}, b_o^{(k)'})$$

$$a_0^{(k)'} = a_0 + \frac{1}{2}$$

$$b_0^{(k)'} = \frac{1}{2} (\mathbb{E}_{g(w)}[w_k^2] + 2b_0)$$

$$q(w) \propto \exp \left\{ \mathbb{E}_{\tilde{y}(w)} [\log p(y | x, \alpha, d, w, x)] + \log q(w) \right\}$$

$$\propto \exp \left\{ \mathbb{E}_{g(x)} \left[-\frac{\lambda}{2} (y - x^T w)^T (y - x^T w) \right] + \mathbb{E}_{g(\alpha_{1:d})} \left[-\frac{\text{diag}(\alpha_{1:d})}{2} w^T w \right] \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \omega^T \left(\mathbb{E}_{g(x)} [Y] X X^T + \mathbb{E}_{g(x;d)} [\text{diag}(\alpha, \dots, \alpha_d)] \right) \omega - \alpha \omega^T \mathbb{E}_{g(x)} [Y] X y \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left(\omega^T \left(\mathbb{E}_{g(x)} [\lambda] X X^T + \mathbb{E}_{g(\alpha_{1:d})} [\text{diag}(\alpha_1, \dots, \alpha_d)] \right) \omega - 2 \omega^T \left(\mathbb{E}_{g(x)} [\lambda] X X^T + \mathbb{E}_{g(\alpha_{1:d})} [\text{diag}(\alpha_1, \dots, \alpha_d)] \right) \mathbb{E}_{g(x)} [\lambda] \left(\mathbb{E}_{g(x)} [\lambda] X X^T + \mathbb{E}_{g(\alpha_{1:d})} [\text{diag}(\alpha_1, \dots, \alpha_d)] \right)^{-1} X y + \left[\mathbb{E}_{g(x)} [\lambda] \left(\mathbb{E}_{g(x)} [\lambda] X X^T + \mathbb{E}_{g(\alpha_{1:d})} [\text{diag}(\alpha_1, \dots, \alpha_d)] \right)^{-1} X y \right]^T \right.$$

$$\bullet \left(\mathbb{E}_{g(x)} [X] X^T + \mathbb{E}_{g(x,d)} [\text{diag}(d, \dots, d)] \right)$$

$$\bullet (E_{g(x)} (E_{g(x)}^T X X^T + E_{g(x,d)}^{(\text{diag}(d, \dots, d))})^{-1} X y)$$

Defining $A = (\mathbb{E}_{g(x)}[x]x^T + \mathbb{E}_{g(x,d)}[\text{diag}(d, \dots, d)])$ just for readability:

$$q(\omega) \propto \left\{ -\frac{1}{2} \left(\omega^T A \omega - 2 \omega^T A \mathbb{E}_{q(x)} [x] A^{-1} x y + (\mathbb{E}_{q(x)} [x] A^{-1} x y)^T A (\mathbb{E}_{q(x)} [x] A^{-1} x y) \right) \right\}$$

$$q(w) = \text{Normal} \left(E_{g(x)} [\mu] \left(E_{g(x)} [\mu] X X^T + E_{g(\alpha, d)} [\text{diag}(\alpha, \dots, \alpha_d)] \right)^{-1} X y, \right. \\ \left. \left(E_{g(x)} [\mu] X X^T + E_{g(\alpha, d)} [\text{diag}(\alpha, \dots, \alpha_d)] \right)^{-1} \right)$$

$$q(\omega) = N(E_{g(x)}[\lambda] A^{-1} x y, A^{-1})$$

$$\mu' = E_{g(x)}[\lambda] A^{-1} x y$$

$$\Sigma^{-1} = A^{-1} = (E_{g(x)}[\lambda] x x^T + E_{g(\alpha, d)}[\text{diag}(\alpha, \dots, \alpha_d)])^{-1}$$

Defining expectations that have been used and are needed to update the various q distributions:

$$(1) E_{g(\alpha, d)}[\text{diag}(\alpha, \dots, \alpha_d)] = \text{diag}(a_0^{(1)'} / b_0^{(1)'}, \dots, a_0^{(d)'} / b_0^{(d)'})$$

$$(2) E_{g(x)}[\lambda] = l_0' / f_0'$$

$$(3) E_{g(\omega_k)}[\omega_k^2] = (E_{g(\omega)}[\omega])^2_k + (E_{g(x)}[\lambda] x x^T + E_{g(\alpha, d)}[\text{diag}(\alpha, \dots, \alpha_d)])^{-1}$$

$$(4) E_{g(\omega)}[\omega \omega^T] = (E_{g(x)}[\lambda] x x^T + E_{g(\alpha, d)}[\text{diag}(\alpha, \dots, \alpha_d)])^{-1} + E_{g(\omega)}[\omega] E_{g(\omega)}^T$$

$$(5) E_{g(\omega)}[\omega] = E_{g(x)}[\lambda] (E_{g(x)}[\lambda] x x^T + E_{g(\alpha, d)}[\text{diag}(\alpha, \dots, \alpha_d)])^{-1} x y$$

(b)

Step 1: Initialize prior parameters $a'_0, b'_0, e'_0, f'_0, \mu'_0$ and Σ'_0

Step 2: For iteration $t=1, \dots, T$

(i) Update $g(x)$:

$$-e'_t = \frac{N}{2} + e_0$$

$$-f'_t = \frac{1}{2} \left(y^T y - 2y^T x^T (\mu_{t-1}) + \text{tr} \left((\Sigma_{t-1} + \mathbb{E}_{g(w)}[w_t] \mathbb{E}_{g(w)}[w]^T) \right) \right)$$

(ii) Update $g(\alpha_k)$:

$$-a_t^{(k)'} = \frac{1}{2} + a_0$$

$$-b_t^{(k)'} = \frac{1}{2} \left(\mathbb{E}_{g(w)}[w_t] \right)^2_{kk} + (\Sigma_{t-1})_{kk}$$

(iii) Update $g(w)$: $A = \left(\mathbb{E}_{g(x)}[x] x^T + \mathbb{E}_{g(\alpha_{1:d})}[\text{diag}(\alpha_1, \dots, \alpha_d)] \right)$

$$-A_t' = \mathbb{E}_{g(x)}[x_t] x_t^T + \mathbb{E}_{g(\alpha_{1:d})}[\text{diag}(\alpha_1, \dots, \alpha_d)_t]$$

$$-\Sigma_t' = A_t^{-1}$$

$$-\mu_t' = \mathbb{E}_{g(x)}[x_t] A_t^{-1} x^T y$$

(iv) Calculate the variational objective function, ELBO

$$\mathcal{L}(a'_t, b'_t, e'_t, f'_t, \mu'_t, \Sigma'_t)$$

$$(c) \mathcal{L}((a_t^{(1)'}, b_t^{(1)'})', \dots, (a_t^{(d)'}, b_t^{(d)'})', e_t', f_t', \mu_t', \xi_t')$$

$$= \int_{\omega} \int_{\lambda} \int_{\alpha_{1:d}} g(\omega) g(\lambda) \frac{\prod_{k=1}^d g(\alpha_k) \ln \frac{P(\omega, \alpha_{1:d}, \lambda | Y, X)}{g(\omega) g(\lambda) \prod_{k=1}^d g(\alpha_k)}}{g(\omega) g(\lambda) \prod_{k=1}^d g(\alpha_k)} d\alpha_{1:d} d\lambda d\omega$$

$$= \int_{\omega} \int_{\alpha_{1:d}} g(\omega) \overset{(1)}{h p(\omega)} d\alpha_{1:d} d\omega + \int_{\lambda} g(\lambda) \overset{(2)}{h p(\lambda)} d\lambda + \int_{\alpha_{1:d}} \frac{d}{\prod_{k=1}^d} g(\alpha_k) \overset{(3)}{h p(\alpha_k)} d\alpha_{1:d} \\ + \int_{\omega} \int_{\lambda} g(\omega) g(\lambda) \overset{(4)}{h p(Y | \omega, \lambda, X)} d\lambda d\omega - \int_{\omega} g(\omega) \overset{(5)}{h g(\omega)} d\omega \\ - \int_{\lambda} g(\lambda) \overset{(6)}{h g(\lambda)} d\lambda - \int_{\alpha_{1:d}} \frac{d}{\prod_{k=1}^d} g(\alpha_k) \overset{(7)}{h g(\alpha_k)} d\alpha_{1:d}$$

$$\text{Eqn (1): } g(\omega) h p(\omega)$$

$$\int_{\omega} \int_{\alpha_{1:d}} g(\omega) h p(\omega) d\omega = -\frac{d}{2} \ln(2\pi) + \frac{1}{2} \sum_{k=1}^d \mathbb{E}_{\alpha_{1:d}} [\ln(\alpha_k)] - \frac{1}{2} \mathbb{E}_{g(\omega), g(\alpha_{1:d})} [\omega_t^T \text{diag}(\alpha_{1:d}) \omega_t] \\ = -\frac{d}{2} \ln(2\pi) + \frac{1}{2} \sum_{k=1}^d (\psi(a_t^{(k)'}) - \ln(b_t^{(k)'})) - \frac{1}{2} \text{tr}((\mu_t' \mu_t'^T + \xi_t') \mathbb{E}_{g(\alpha_{1:d})} [\text{diag}(\alpha_{1:d})])$$

$$\text{Eqn (2): } g(\lambda) h p(\lambda)$$

$$\int_{\lambda} g(\lambda) h p(\lambda) d\lambda = e_0 \ln(f_0) - \ln(f(e_0)) + (e_0 - 1) \mathbb{E}_{g(\lambda)} [\ln \lambda] - \int_0^{e_0} \mathbb{E}_{g(\lambda)} [\lambda]$$

$$= e_0 \ln(f_0) - \ln(f(e_0)) + (e_0 - 1) (\psi(e_t') - \ln(f_t')) - \int_0^{e_t'} \frac{e_t'}{f_t'}$$

$$\text{Eqn (3): } \frac{d}{\prod_{k=1}^d} g(\alpha_k) \ln p(\alpha_k) d\alpha_{1:d}$$

$$\int_{\alpha_{1:d}} \frac{d}{\prod_{k=1}^d} g(\alpha_k) \ln(p(\alpha_k)) d\alpha_{1:d} = \int_{\alpha_{1:d}} \sum_{k=1}^d g(\alpha_k) \ln(p(\alpha_k)) d\alpha_k$$

$$= \sum_{k=1}^d \int_{\alpha_k} g(\alpha_k) \ln(p(\alpha_k)) d\alpha_k$$

$$= \sum_{k=1}^d a_0 \ln(b_0) - \ln(\Gamma(a_0)) + (a_0 - 1) (\psi(a_0^{(k)'}) - \ln(b_t^{(k)'})) - b_0 \frac{a_t^{(k)'}}{b_t^{(k)'}}$$

$$\text{Eqn (4): } g(w) \ln(w) dw$$

$$\int_w g(w) \ln(w) dw = \frac{1}{2} \ln((2\pi e)^n | \Sigma_t |)$$

$$\text{Eqn (5): } g(x) \ln(x) dx$$

$$\begin{aligned} \int_x g(x) \ln(x) dx &= e_t' \ln(f_t') - \ln(\Gamma(e_t')) + (e_t' - 1) (\psi(e_t') - \ln(f_t')) - \int_t' \frac{e_t'}{f_t'} \\ &= \ln(f_t') - \ln(\Gamma(e_t')) + (e_t' - 1) \psi(e_t') - e_t' \end{aligned}$$

$$\text{Eqn (6): } \frac{d}{\prod_{k=1}^d} g(\alpha_k) \ln(g(\alpha_k))$$

$$\int_{\alpha_{1:d}} \frac{d}{\prod_{k=1}^d} g(\alpha_k) \ln g(\alpha_k) d\alpha_{1:d} = \sum_{k=1}^d \ln(b_t^{(k)'}) - \ln(\Gamma(a_t^{(k)'}) + (a_t^{(k)' - 1}) \psi(a_t^{(k)'}) - a_t^{(k)'}$$

$$\text{Eqn (7): } q(w)q(x) \ln(p(y|w, x, \lambda))$$

$$\int \int q(w)q(x) \ln(p(y|w, \lambda, x)) d\lambda dw$$

$$= -\frac{N}{2} \ln(2\pi) + \frac{N}{2} \left(\mathbb{E}_{q(x)}[\lambda] \right) - \frac{\mathbb{E}_{q(x)}[\lambda]}{2} \mathbb{E}_{q(w)}[w]$$

$$\cdot \left[(y - x^T w)^T (y - x^T w) \right]$$

$$= -\frac{N}{2} \ln(2\pi) + \frac{N}{2} (\psi(e_t) - \ln(f_t')) - \frac{e_t'}{2f_t'} \left[Y^T Y - 2Y^T X^T \mu_t' - \text{tr}((\Sigma_t' + \mu_t' \mu_t'^T) \cdot X X^T) \right]$$

∴ In order to get the entirety of the variational objective function, we must combine the final forms of the 7 parts from the original equation which we have broken down above.

Thus, we have: For ease of readability, the different parts will be different colors:

$$\mathcal{L}((a_t^{(u)}, b_t^{(u)'}) \dots (a_t^{(d)}, b_t^{(d)'}), e_t', f_t', \mu_t', \Sigma_t') =$$

$$= -\frac{d}{2} \ln(2\pi) + \frac{1}{2} \sum_{k=1}^d (\psi(a_t^{(k)'}) - \ln(b_t^{(k)'})) - \frac{1}{2} \text{tr}((\mu_t' \mu_t'^T + \Sigma_t') \mathbb{E}_{g(a_1, d)} [\text{diag}(a_1, \dots, a_d)])$$

$$+ e_0 \ln(f_0) - \ln(\Gamma(e_0)) + (e_0 - 1) (\psi(e_t') - \ln(f_t')) - f_0 \frac{e_t'}{f_t'}$$

$$+ \sum_{k=1}^d a_0 \ln(b_0) - \ln(\Gamma(a_0)) + (a_0 - 1) (\psi(a_t^{(k)'}) - \ln(b_t^{(k)'})) - b_0 \frac{a_t^{(k)'}}{b_t^{(k)'}}$$

$$+ \frac{1}{2} \ln((2\pi e)^n |Z_t|)$$

$$- \left\{ \ln(f_t') - \ln(\Gamma(e_t')) + (e_t' - 1) \psi(e_t') - e_t' \right\}$$

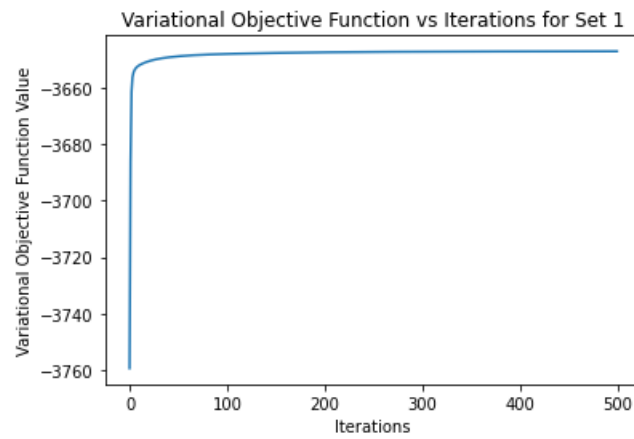
$$- \left\{ \sum_{k=1}^d \ln(b_t^{(k)'}) - \ln(\Gamma(a_t^{(k)'})) + (a_t^{(k)'} - 1) \psi(a_t^{(k)'}) - a_t^{(k)'} \right\}$$

$$= \left\{ -\frac{N}{2} \ln(2\pi) + \frac{N}{2} (\psi(e_t') - \ln(f_t')) - \frac{e_t'}{2f_t'} \left[Y^T Y - 2 Y^T X^T \mu_t' - \text{tr}((Z_t' + \mu_t' \mu_t'^T) \cdot X X^T) \right] \right\}$$

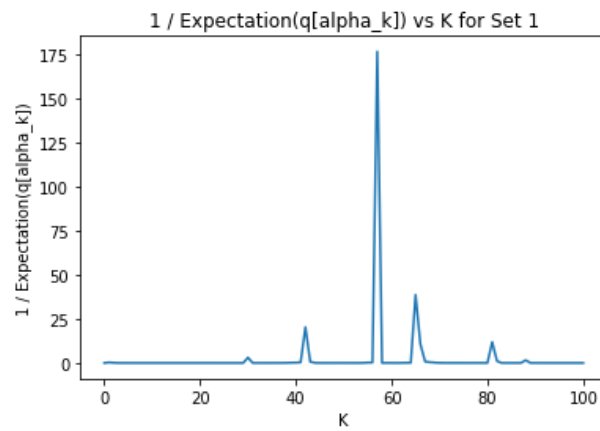
Thus, with the above ELBO, we can check the convergence of our pseudo-code algorithm in part b above.

Question 2:

Part A (Set 1)



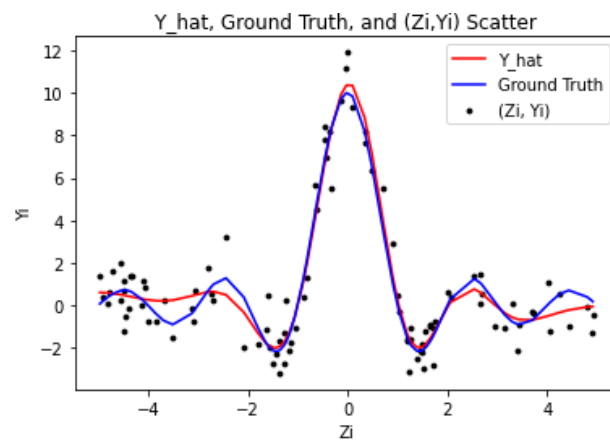
Part B (Set 1)



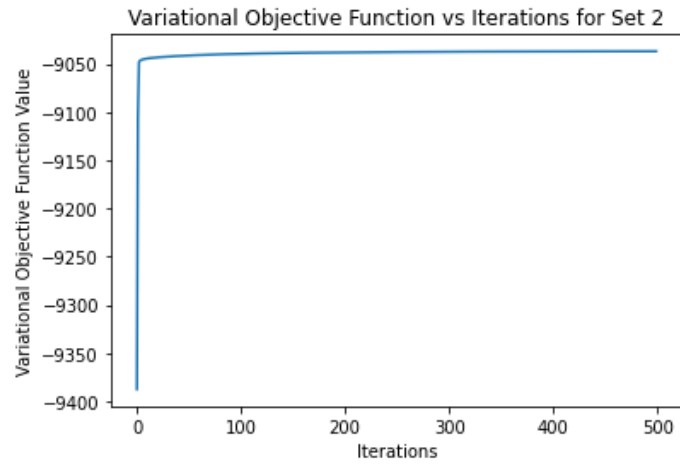
Part C (Set 1)

`1/E_q[lambda] for Set 1 = [[1.01909983]]`

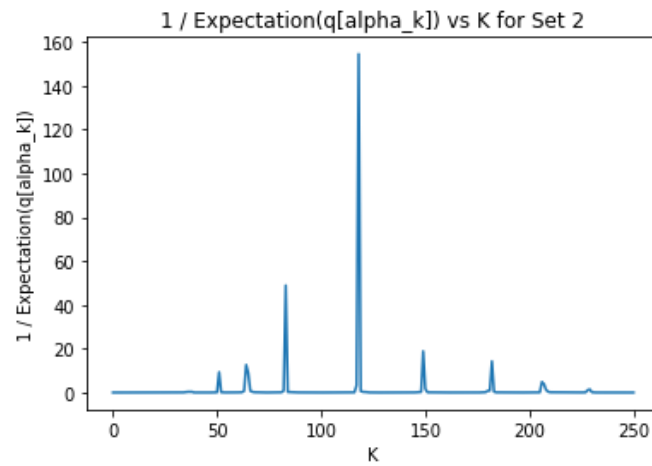
Part D (Set 1)



Part A (Set 2)



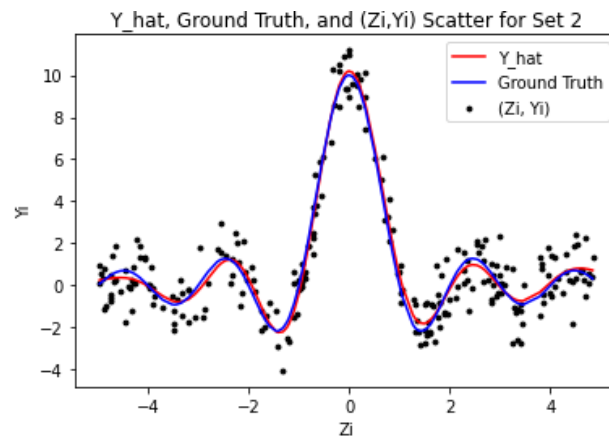
Part B (Set 2)



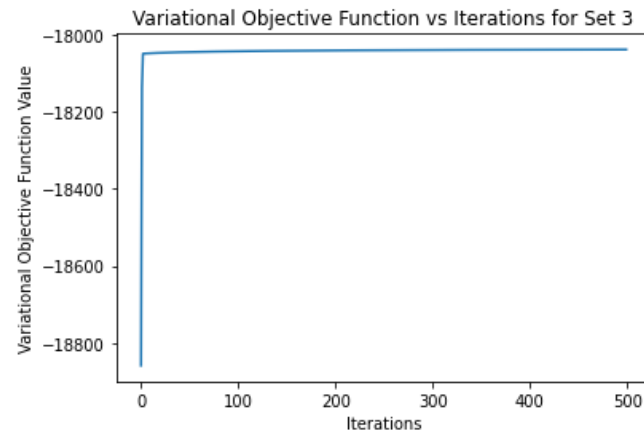
Part C (Set 2)

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1/E_q[lambda] for Set 2 = [[0.90035679]]
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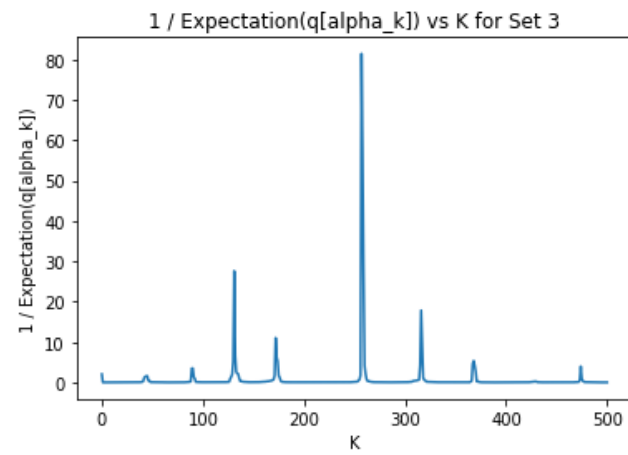
Part D (Set 2)



Part A (Set 3)



Part B (Set 3)



Part C (Set 3)

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1/E_q[lambd] for Set 3 = [[0.972746]]
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Part D (Set 3)

